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EXAMINING INTERINDIVIDUAL DIFFERENCES IN CYCLICITY OF PLEASANT AND UNPLEASANT AFFECTS USING SPECTRAL ANALYSIS AND ITEM RESPONSE MODELING

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Weekly cycles in emotion were examined by combining item response modeling and spectral analysis approaches in an analysis of 179 college students' reports of daily emotions experienced over 7 weeks. We addressed the measurement of emotion using an item response model. Spectral analysis and multilevel sinusoidal models were used to identify interindividual differences in intraindividual cyclic change. Simulations and incomplete data designs were used to examine how well this combination of analysis techniques might work when applied to other practical data problems. Empirically, we found systematic individual differences in the extent to which individuals' emotions follow a weekly cycle, and in how such cycles are exhibited. Weekly cycles accounted for very little variance in day to day emotions at the individual level. Analytically, we illustrate how measurement, change, and interindividual difference models from different traditions may be combined in a practical manner to describe some of the complexities of human behavior.

Key words: non-linear, multilevel, longitudinal, missing data, emotion.

Several studies have found that emotions vary with the days of the week (e.g., Egloff, Tausch, Kohlmann, & Krohne, 1995; Kennedy-Moore, Greenberg, Newman, & Stone, 1992; Larsen &

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Kasimatis, 1990; McFarlane, Martin, & Williams, 1988; Stone, Hedges, Neale, & Satin, 1985). McFarlane et al. (1988), for example, found that moods tend to be lowest on Mondays (i.e., "Blue Monday"). In contrast, when examining both positive and negative moods, Stone et al. (1985) concluded that "Blue Mondays" were the result of a post-weekend decline in positive moods, rather than a Monday increase in negative moods.

Larsen and Kasimatis (1990) explicitly modeled the day-to-day progression of emotions using spectral analysis. They found that a 7-day sinusoidal cycle accounted for about 40% of the variance in aggregated mood scores (i.e., within-occasion across person means) over time—providing evidence that, at the group level, emotions differ from day to day and likely follow a weekly cycle. At the individual level, however, they found substantial differences in how entrained particular persons were to a weekly cycle, with individuals high on extraversion showing less evidence of systematic weekly patterns in their emotions than individuals low on extraversion. Thus, interindividual differences appear to play a role in how emotions progress from day to day.

In this paper we examine the weekly cyclicity of emotions at the individual level in more detail in order to effectively disentangle differences across individuals, variables, and occasions. We analyzed a multivariate, multiperson, multioccasion data set that contained information about individuals' daily emotional experiences for approximately 7 weeks—data from an emotion diary study. Such data can be configured as a three-dimensional, persons $\times$ variables $\times$ occasions, "data-box" (Cattell, 1952). The sections below outline how we approached three practical issues correspondent to these dimensions: measurement (relations among variables), change (relations among occasions), and individual differences (among persons).

Measurement: Multivariate Item Response Models

Often estimates of emotional states are obtained either by summing over multiple items to create a composite score or by conducting a linear factor analysis on the item scores to obtain latent factor scores. However, these methods make rather strong assumptions regarding the spacing of response categories, the relative weightings of items, and/or the characteristics of residuals (usually normality). Item response models offer a way to either relax these assumptions or explicitly test their suitability. In particular, the Rating Scale Model (RSM) (Andrich, 1978) and other Rasch family models for polytomous data (Rost, 2001) can be used to incorporate non-linearity in the spacing of response categories and in the relationship between underlying (latent) trait levels and item responses. Fit statistics assessing the adequacy of the model also allow for testing whether the data conform to the assumptions of the model.

Item response models have most often been used to examine trait levels at a single occasion, under the assumption that the occasion of measurement is irrelevant for understanding individual differences in the trait. In other words, item response models are most often used to examine presumably stable constructs. However, when the "trait" or "state"[1] level changes over time, new issues emerge. A change model must be applied in conjunction with (or incorporated within) the item response model.

Change: Nonlinear, Cyclic, Longitudinal Models

Human emotions and physiological rhythms have been found to display some regular, predictable nonlinear changes over time. These include circadian rhythms, menstrual cycles, and seasonal changes in mood (e.g., Larsen & Kasimatis, 1990; Murray, Allen, Trinder, & Burgess,

[1]In much of the item response literature, the latent construct being measured is referred to as a "trait," indicating underlying notions of stability. We, being interested in a construct that is constantly changing, have attempted to apply item response models, originally developed for the measurement of (stable) "trait" constructs, to the measurement of (changing) "state" constructs. To highlight that the approach is being used to measure labile or changing constructs we have replaced the usual "trait" terminology with "state" terminology throughout the manuscript.

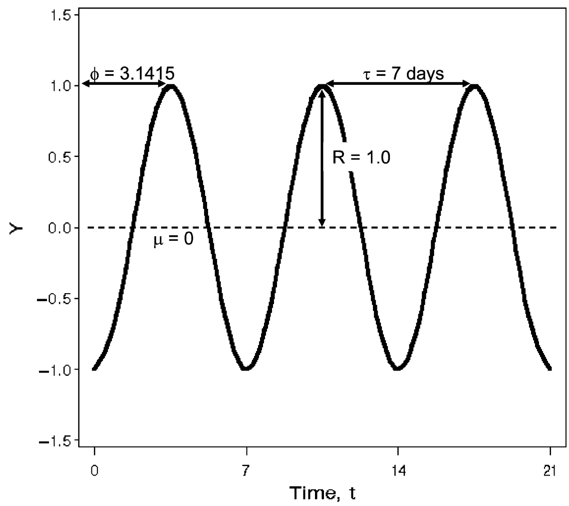

FIGURE 1.
Basic sine wave. The bold line represents a time series Y_t for a single subject measured from time $t = 0$ to 28, $R =$ amplitude of oscillation, $\tau =$ period of oscillation, μ is the mean of the oscillation (or vertical shift), and ϕ is the phase (horizontal) shift or time elapsed between time 0 and the first peak of the wave.

2002; Reid, Towell, & Golding, 2000; Rusting & Larsen, 1998). One basic model of nonlinear change is cyclic change—generally represented by a sinusoidal function, depicted in Figure 1, and expressed as:

$$Y_t = \mu + \beta t + R[\cos(\omega t + \phi)] + \varepsilon_t, \tag{1}$$

where Y_t is a time-series measured from time $t = 0$ to T for a single subject, β represents the general linear trend in the time-series (and included here only for detrending purposes), R is the amplitude of oscillation, $\omega = 2\pi/\tau$ is a particular frequency of oscillation in radians and τ the period of oscillation (in units of t), μ is the mean of the oscillation (or vertical shift), ϕ is the phase (horizontal) shift of the oscillation or time elapsed between time 0 and the first peak of the wave, and ε_t is a time series of normally distributed residuals.

Cyclic change is usually examined using frequency-domain time-series methods (Box & Jenkins, 1976; Koopmans, 1995; Warner, 1998). In short, this class of methods can be used to extract and represent the cycles or oscillations present in single-subject multioccasion data. As a whole, frequency-domain analysis techniques range from the more "exploratory" spectral analysis to the more "confirmatory" fitting of a particular sinusoid. In the latter, a prespecified frequency (e.g., the frequency associated with a weekly cycle) is directly fitted to the data in much the same way as a linear function is fitted to the data in a regression analysis. By assessing how well the model fits the data (e.g., the amount of variance explained), we can assess the extent to which an individual's data are characterized by, or "entrained" to the hypothesized cyclic process. Spectral analysis, in contrast, can be used to fit a collection of frequencies to each individual's data, and, in an exploratory way, identify those frequencies that are most prominent.

Interindividual Differences

In the sections above, we outlined how we approached the examination of patterns in the relationships among variables (i.e., measurement of latent "states") and among occasions (modeling cyclic change). We were also interested in how individuals differed in the day-to-day progression of emotions. Note, however, that interindividual differences may be incorporated into the analysis at multiple levels. Following the growth modeling tradition, we examined *individual* *differences* in the parameters characterizing the intraindividual cyclicity of daily emotion. We assumed that the measurement model (i.e., RSM item characteristics) did not differ across persons or occasions and that the functional form of the change model (i.e., cyclic change) did not differ across persons. Only the parameters describing particular aspects of cyclic change (e.g., amplitude R, phase ϕ) were allowed to differ between persons.

Model Selection

From an analytic perspective, there are numerous measurement, change, and individual difference models that can be used in combination. Our selection of models was driven by theory, data, and practicality. We used an item response *measurement* model to obtain "true score" estimates of individuals' current "states" that had desirable measurement properties. We examined the day-to-day *change* in individuals' "states" using frequency-domain analysis techniques that matched theoretical notions regarding weekly cycles. More specifically, we used spectral analysis to explore what cycles characterized each individual's pleasant affect (PA) and unpleasant affect (UA) and used multilevel models of change to examine *individual differences* in the intraindividual cyclicity of daily emotion.

Combining and Fitting Measurement, Change, and Interindividual Difference Models

While constructing a single model that invokes our notions about the item response (measurement) process, the change process, and the nature of individual differences is theoretically appealing, fitting such a comprehensive (read complicated) model and testing it against the data can be quite difficult. Advances in statistical theory (e.g., latent regression), estimation algorithms, and computer technology, however, have made doing so possible. For instance, item responses, "state" changes, and individual differences can all be combined within the dynamic generalized multilevel mixed model (Fahrmeir & Tutz, 2001) and estimated simultaneously using specialized software (e.g., SAS Proc Nlmixed; WinBUGS; Spiegelhalter, Thomas, Best, & Lunn, 2003).

A practical alternative is to simplify the accessibility and estimation of such models by using multistep procedures. For instance, one might first estimate individuals' latent "state" at each measurement occasion using an item response model. Second, the hypothesized model of change could be used to model the changes in "state" level across measurement occasions and the interindividual differences therein. This two-step examination process is relatively easy to implement using standard software and has yielded some interesting and interpretable results (Bond & Fox, 2001; Dawson, 2000; Lee, 2003; McArdle, Grimm, Hamagami, Bowles, & Meredith, 2005; McArdle & Hamagami, 2004). Here we examine the weekly cyclicity of emotional states using both simultaneous and multistep fitting of combined item response, cyclic change, and interindividual difference models.

Simulation

In order to assess the practical utility of the combined item response modeling the spectral analytic approach, we first examined whether or not the method was able to recover the measurement, change, and interindividual differences in simulated data. Specifically, we simulated data to reflect our hypothesized model—that individuals' emotions are in part determined by a weekly cycle. We then attempted to recover the characteristics of the measurement model, the cyclic model, and interindividual differences therein.

Incomplete Data

When taking part in emotion diary studies participants often bear quite a burden—completing a multitude of items over and over again. In the present study, for instance, participants responded to more than 40 items, daily, for 52 consecutive days. Providing complete data required the completion of over 2000 total items. Furthermore, in such a study participants usually respond to the same set of items many times. Although similar burdens have been successfully borne by participants in other longitudinal studies of emotion, it is possible, perhaps probable, that items are not approached with the same cogency on the 50th occasion as on the 1st or 2nd occasion (e.g., there may be some "item drift"). The amount of effort and time that participants must expend in providing data that can inform our particular inquiries often poses difficulties in recruitment and retainment. Thus, because longitudinal data is often incomplete (i.e., missing) we also examined if the analytic method was able to identify interindividual differences when the data had different amounts or kinds of incompleteness. We examined how the technique worked under various missing-at-random data conditions and under planned incomplete data design conditions that might effectively reduce data collection costs.

To summarize, we examined weekly cycles in emotion by combining item response modeling and spectral analytic approaches in our analysis of multivariate, multiperson, longitudinal (diary) emotion data. The measurement of emotion was addressed using an item response model from the Rasch family (RSM) (Andrich, 1978). Frequency-domain analytic techniques were used to identify interindividual differences in cyclic change. Finally, simulation and incomplete data designs were used to examine how well this combination of analytic techniques might work when applied to other practical data problems.

1. Method

1.1. Participants and Measures

The participants were 179 college students (98 males, 81 females, mean age = 20.24, *SD* = 1.81) enrolled in a semester-long course (Fall 1991 or Spring 1992) at the University of Illinois on subjective well-being research. As part of their course exercises, these students/participants completed numerous self-report personality and affect measures. One of the assignments was to provide daily self-reports of their emotional experiences for 52 consecutive days. Participants were asked to rate how often they felt each of 40 emotions on a 7-point Likert-type scale with 1 representing none, and 7 representing always. Based on previous factor analyses of these emotion ratings (Diener, Smith, & Fujita, 1995) we selected eight items as markers of pleasant affect (PA: love, affection, caring, fondness, joy, happiness, contentment, and satisfaction) and eight items as markers of unpleasant affect (UA: depression, unhappiness, shame, nervousness, loneliness, sadness, anxiety, and irritation) for this study. Further details regarding the larger study and other analyses of the data can be found elsewhere (see Chow, Ram, Boker, Fujita, & Clore, 2005; Diener, et al., 1995; Eid & Diener, 1999).

1.2. Data Analysis and Models

1.2.1. Rating scale (RSM) *measurement model.* In the main analysis we fitted the RSM (Andrich, 1978) in order to evaluate the measurement properties of our eight-item PA and UA scales and to obtain "true score" estimates of individuals' level of PA and UA at each occasion. The RSM for J items each with m categories $(1, 2, \ldots, m)$ is written as

$$P(X_{itj} = x \mid \theta_{it}, \lambda_j, \delta) = \frac{\exp\left\{\sum_{k=2}^{x} [\theta_{it} - (\lambda_j + \delta_k)]\right\}}{1 + \sum_{z=2}^{m} \exp\left\{\sum_{k=2}^{z} [\theta_{it} - (\lambda_j + \delta_k)]\right\}}, \tag{2}$$

$$\text{where} \quad \sum_{k=2}^{x}[\theta_{it} - (\lambda_j + \delta_k)] = 0 \quad \text{when} \quad x = 1, \quad \sum_{k=2}^{m}\delta_k = 0, \quad \text{and} \quad \sum_{j=1}^{J}\lambda_j = 0.$$

$P(X_{itj} = x \mid \theta_{it}, \lambda_j, \delta)$ is the probability of a response in category x by individual i at time t on item j conditional on the individual's level of the construct at time t, (θ_{it}), the difficulty of item j, (λ_j), and a set of $m - 1$ thresholds between categories, $(\delta = \{\delta_2, \delta_3, \ldots, \delta_m\})$.

Briefly, the RSM models the probability that an individual will respond to a particular item using a particular category (1 to 7), given their current level of affect. Item difficulty is a reflection of the general level of the underlying construct the item is most effective at measuring. For instance, some items may discern differences between low "state" levels of affect (e.g., happy), while other items may be more attuned to fine differences at the higher end of the scale (e.g., ecstatic). As a person's "state" level increases, they will, with some probability, respond using a higher category. The thresholds between categories may be unevenly spaced and items may be of differing difficulties. However, the set of $m - 1$ category thresholds is assumed to hold across all items and the difficulty of any item j is assumed to be invariant over time.

The model was fit to all participants' PA item responses across all measurement occasions simultaneously. Thus, the model defines and describes the measurement characteristics of the items that hold for all persons and occasions. The same procedure was repeated using the UA responses.

1.2.2. An alternative composite score measurement model. For purposes of illustration and comparison to previous research we also used a composite score measurement model to obtain PA and UA scores. This model takes the form

$$\theta_{it} = \frac{\sum\limits_{j=1}^{J} X_{itj}}{J}, \tag{3}$$

where θ_{it} is the average response individual i gave at time t on J items. Using composite scores brings with it a restrictive theory about how individuals respond to items and may lead to inaccuracies in "true" score estimation if incorrect (see Wright, 1984, 1997 for an in-depth discussion).

1.2.3. Interindividual differences in change model. The "state" estimates of PA and UA derived from the RSM (and composite score measurement model) were used as the input time-series data for the analyses of cyclic change. Spectral analysis (Proc Spectra in SAS) was conducted on the individual detrended PA and UA time series shown in Figures 2 and 3. We noted the dominant cycle in each series (i.e., the sinusoidal frequency that accounted for the most variance in an individual's PA or UA series) and summarized this information across individuals.

Subsequently, we used a multilevel model of change to examine interindividual differences in the weekly cyclicity of PA and UA. Re-expressing equation (1) to include multiple persons, the model of change was

$$\theta_{it} = \mu_i + \beta_i t_{it} + R_i[\cos(\omega t_{it} + \phi_i)] + \varepsilon_{it}, \tag{4}$$

where ω is fixed to $2\pi/7$ in order to model the 7-day or weekly cycle, μ_i is an intercept for individual i, β_i is the individual's linear slope (to remove linear trends), R_i is the amplitude of his or her weekly cycle, ϕ_i is the phase shift representing which day of the week the cycle peaks for that individual, and ε_{it} are normally distributed within-person residuals. Interindividual

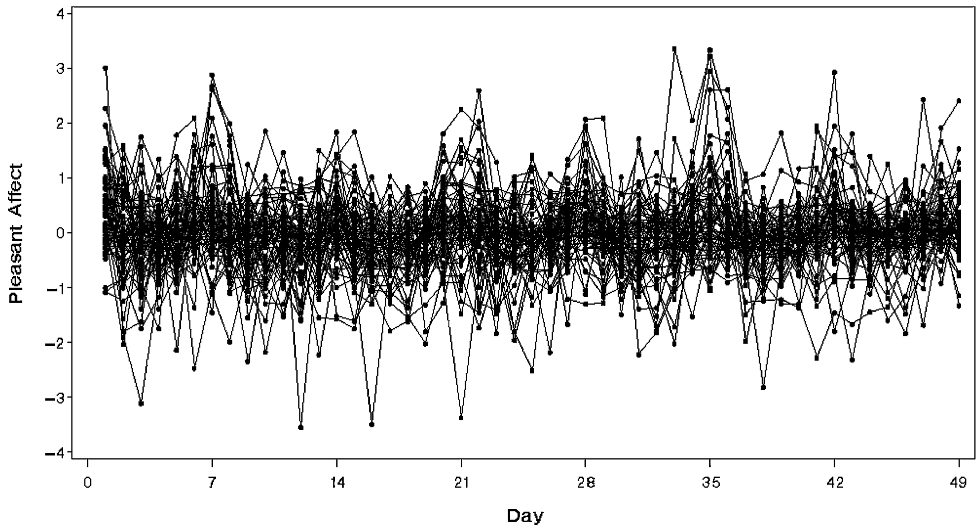

FIGURE 2.
PA "state" estimates across time derived from the RSM (detrended). Each individual is represented by a single line connecting their day to day emotional experiences.

differences in change parameters were modeled as

$$\mu_i = \gamma_{00} + u_{0i}, \tag{5}$$

$$\beta_i = \gamma_{10} + u_{1i}, \tag{6}$$

$$R_i = \gamma_{20} + u_{2i}, \tag{7}$$

$$\phi_i = \gamma_{30} + u_{3i}, \tag{8}$$

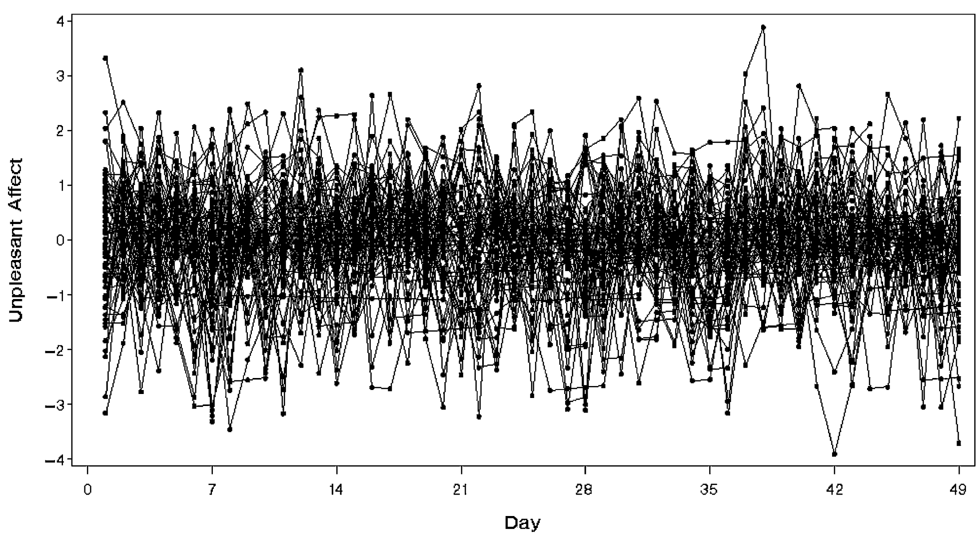

FIGURE 3.
UA "state" estimates across time derived from the RSM (detrended). Each individual is represented by a single line connecting their day to day emotional experiences.

where γ_{00}, γ_{10}, γ_{20}, γ_{30} are the sample means of the change model parameters and u_{0i}, u_{1i}, u_{2i}, u_{3i} are individual deviations from those means that are normally distributed and may be correlated. Note that although μ_i and β_i are important parts of the model, we use them here only for detrending purposes and do not interpret them. We concentrate only on interindividual differences in the parameters specific to weekly cyclic change, R_i and ϕ_i.

1.2.4. Combined model. Replacing the interindividual differences in the change model for θ_{it}, equations (5) to (9), within the measurement model, equation (2), we obtain the full "combined" weekly cycle model—the articulation of a particular theory about how interindividual differences in the weekly cyclicity of emotion may be observed in a set of multivariate (multicategory), multioccasion, multiperson data. This "combined" model, with nonlinearity incorporated in the measurement model and in the change model, was fitted to data using two approaches. In the "simultaneous" approach WinBUGS (Spiegelhalter et al., 2003), a flexible software program for fitting statistical models using Bayesian and Markov Chain Monte Carlo (Gibbs sampling) methods, was used to fit the combined model all at once (see also Fox & Glas, 2001).[2] As a practical alternative, we also fitted the combined model to the data using a "multistep" process. First, individuals' latent "state" level at each measurement occasion, θ_{it}, was estimated and output using the RSM (e.g., implemented here using the Winsteps program, Linacre, 2003). Second, interindividual differences in change (cyclicity) were examined using nonlinear multilevel modeling procedures (implemented here using WinBUGS). Programming, fitting, and convergence details are available from the authors upon request.

1.2.5. Simulation. To confirm that our estimation procedures could yield reasonably accurate estimates of the individual differences in the change process, we simulated data to reflect our hypothesized model—that individuals' emotions are in part determined by a weekly cycle. We simulated "state" levels of emotion for 200 individuals at 49 time points[3] using multiple sinusoidal curves. Each individual's data were the weighted summation of two cyclic patterns, a cycle of 7-day periodicity, and a cycle of another periodicity that ranged from 3 to 17 days. Individuals' simulated "emotional experiences" differed in the predominant period of oscillation (either the 7-day or the additional cycle was weighted more heavily), amplitude of oscillation (range $= 0$ to 1), and phase shift (range $= 0$ to π). Item responses were generated based on the RSM with fixed item parameters that did not differ between persons or occasions. We then analyzed this simulated data in the same manner as we had the empirical data, attempting to recover interindividual differences in the predominant period of oscillation, and amplitude and phase of the 7-day cycle.

1.2.6. Incomplete data. In the final set of analyses we examined how different amounts and patterns of incompleteness might affect our ability to recover the cyclicity in the participants' data. To this end, we systematically removed portions from the complete data set, calculated new "true score" levels of PA and UA using the RSM, and re-ran the frequency-domain analyses as outlined above. We examined two questions.

[2]This approach is similar to that outlined by Fox and Glas (2001) for fitting a multilevel item response theory model using Gibbs sampling. In the present application, however, the "multilevel" portion of the model includes nonlinear regressions (to model cyclicity).

[3]In order to be sure that the cycle length of interest (7 days) was included as one of the Fourier frequencies fitted during the spectral analysis we chose to examine 49 (a multiple of 7) occasions (see Warner, 1998, for further details on the selection of number of occasions).

1.2.7. Can the process of interest be identified even when the data are incomplete? In longitudinal studies missing data often occur when participants are unable or unwilling to take the time to complete measures. Thus, whole occasions of data may be missing (as opposed to missing an item response here and there). To simulate such incompleteness we successively dropped between 10 and 60% of individuals' data (occasions) in a random fashion (i.e., MCAR, see Little & Rubin, 1987) and re-ran our analyses. We then identified the point at which the amount of incomplete data compromised our identification of the "true" results.

1.2.8. Are there ways to effectively reduce the burden placed on participants and still describe the process of interest with accuracy?. We were also interested to know if the interindividual differences in cyclicity could have been identified with shorter questionnaires. We reconfigured the data as though it had been collected using modern experience sampling (e.g., palm pilots) and planned incompleteness designs. Specifically, for each person at each occasion (sampling) we randomly selected two or four items from each of the PA or UA item pools. The data were constructed to reflect a study design wherein at each experience sampling occasion participants were given a small set of randomly selected items. Practically, the items not received on that occasion were treated as "missing" and were accounted for using common person–common item equating (Kolen & Brennan, 1995). Such data collection schemes might eliminate or alleviate the possibility of rote responding patterns (resulting in item drift), would be cost-efficient, and easy for emotion researchers to implement in experience sampling longitudinal (diary) designs.

2. Results

2.1. Measurement and "State" Estimates

RSM results are shown in the top portion of Table 1. We used the standard fit statistics provided by Winsteps to assess the fit of the data to the RSM (see Wright & Masters, 1982, for further details). The PA data fit the RSM well. PA item infit and outfit statistics ranged from 0.70 to 1.32, and from 0.70 to 1.27, respectively, and were within the range of acceptable fit (0.6 to 1.4; Wright & Linacre, 1994). Person and item reliabilities (.88 and 1.00, respectively) also indicated a good fit of the data to the model. The UA items also fit the RSM well. Item infit and outfit statistics ranged from 0.75 to 1.35 and from 0.73 to 1.17. Along with the relatively high person and item reliabilities (0.75 and 1.00) these indices indicated an acceptable fit of the data to the model. Thus, overall, the RSM provided a reasonable measurement model for both the PA and UA item responses across persons and occasions.

The category thresholds (i.e., distances between responses 1, 2, 3, . . ., 7) for the PA items were not evenly spaced (as would have been assumed in a sum composite score or standard factor analysis model). For the PA items, relatively little differentiation was observed among the lower categories (1, 2, 3) and among the middle categories (3, 4, 5), meaning that categories 2 and 4 are rather narrow. For the UA items, relatively little differentiation was observed among the middle categories (3, 4, 5) and at the high end of the scale (5, 6, 7), meaning that again category 4, but now also category 6, are narrow. The nonlinearity in response patterns suggests that the RSM, a model that allows for such nonlinearity, provides what may be a more accurate representation of the response process than might be obtained with composite or standard factor analysis measurement models.

One concern with the UA scale is that the response rate for categories 4 and above was very small, accounting for less than 10% of all responses, while categories 1 (41%) and 2 (33%)

TABLE 1.
Combined Model Results—Simultaneous and Multi-step Approaches.

		PA Simultaneous approach	PA Multistep approach	UA Simultaneous approach	UA Multistep approach
Item Difficulties (*SE* = .01 or .02) [MNSQ Infit, MNSQ Outfit]					
Happiness/Anxiety	λ_1	−0.53	−0.60 [0.81, 0.82]	−0.75	−0.85 [1.06, 1.06]
Contentment/Irritation	λ_2	−0.33	−0.37 [0.95, 0.95]	−0.51	−0.57 [0.93, 0.98]
Caring/Nervous	λ_3	−0.19	−0.22 [0.70, 0.70]	−0.42	−0.47 [1.11, 1.04]
Love/Unhappiness	λ_4	0.09	0.10 [1.19, 1.15]	−0.12	−0.13 [0.75, 0.73]
Satisfied/Loneliness	λ_5	0.09	0.10 [1.08, 1.07]	0.06	0.08 [1.27, 1.15]
Affection/Sadness	λ_6	0.14	0.16 [0.83, 0.82]	0.20	0.22 [0.90, 0.86]
Fondness/Depression	λ_7	0.20	0.23 [1.08, 1.18]	0.45	0.51 [1.09, 0.91]
Joy/Shame	λ_8	0.53	0.59 [1.32, 1.27]	1.09	1.21 [1.35, 1.17]
Response Category Thresholds (*SE* = .01 or .02)					
1–2	δ_1	−1.75	−2.00	−2.12	−2.48
2–3	δ_2	−1.34	−1.49	−1.04	−1.13
3–4	δ_3	−0.10	−0.15	0.19	0.21
4–5	δ_4	0.10	0.12	0.38	0.48
5–6	δ_5	1.03	1.16	1.09	1.24
6–7	δ_6	2.02	2.36	1.50	1.69
Weekly Cycle Fixed Effects (*SE*)					
Level, μ_i	γ_{00}	−0.40 (.066)	−0.46 (.077)	−1.93 (.070)	−2.25 (.082)
Linear change, β_i	γ_{10}	0.00 (.002)	−0.00 (.002)	−0.01 (.002)	−0.01 (.002)
Amplitude, R_i	γ_{20}	0.17 (.016)	0.19 (.019)	−0.06 (.020)	−0.09 (.022)
Phase shift, ϕ_i	γ_{30}	0.24 (.075)	0.24 (.079)	−0.09 (.103)	−0.01 (.136)
Weekly Cycle Variance Components (*SE*)					
Within-person, ε_t	$\sigma^2{}_{\varepsilon}$	0.43 (.006)	0.43 (.005)	0.58 (.009)	0.86 (.007)
In level, u_{0i}	$\sigma^2{}_0$	0.78 (.090)	1.03 (.116)	0.79 (.087)	1.13 (.129)
In linear change, u_{1i}	$\sigma^2{}_1$	0.01 (.000)	0.01 (.000)	0.01 (.000)	0.01 (.000)
In amplitude, u_{2i}	$\sigma^2{}_2$	0.03 (.005)	0.04 (.007)	0.04 (.008)	0.05 (.010)
In phase shift, u_{3i}	$\sigma^2{}_3$	0.07 (.025)	0.06 (.030)	0.15 (.071)	0.13 (.053)
Covariance, u_{0i}, u_{1i}	σ_{01}	−0.00 (.002)	−0.00 (.002)	−0.00 (.002)	−0.00 (.003)
Covariance, u_{0i}, u_{2i}	σ_{02}	−0.01 (.015)	−0.00 (.020)	−0.01 (.019)	−0.02 (.025)
Covariance, u_{0i}, u_{3i}	σ_{03}	0.05 (.046)	0.04 (.061)	0.08 (.101)	0.12 (.129)
Covariance, u_{1i}, u_{2i}	σ_{12}	−0.00 (.000)	0.00 (.001)	0.00 (.000)	0.00 (.001)
Covariance, u_{1i}, u_{3i}	σ_{13}	−0.00 (.001)	0.00 (.001)	−0.00 (.001)	−0.00 (.001)
Covariance, u_{2i}, u_{3i}	σ_{23}	−0.02 (.008)	−0.02 (.011)	−0.06 (.018)	−0.05 (.018)

TABLE 1.
Continued.

	PA Simultaneous approach	PA Multistep approach	UA Simultaneous approach	UA Multistep approach
Percentage of Variance Accounted for in Individual Series by Weekly Cycle[5]				
	PA		UA	
Mean (SD)	6.3% (10.3)		3.0% (4.8)	
Correlation between "Simultaneous" and "Multistep" Findings				
	PA r_{SM}		UA r_{SM}	
Amplitude, R_i	.99		.95	
Phase shift, ϕ_i	.97		.92	

Note. Numbers in parentheses = standard errors of the posterior distribution of the associated parameter, (*SE*). If not shown SE = .01 or .02. Numbers in brackets = mean square infit and outfit statistics of item parameters [MNSQ infit, MNSQ outfit]. *SD* = standard deviation. r_{SM} = correlations between individual difference parameters obtained from the two estimation approaches.

were used for the bulk of the responses. Therefore, most of the information in the UA items is contained in the threshold between categories 1 and 2 and, as a result, the standard error of UA measurements is, in general, higher than for the PA measurements (for which category usage was more evenly spread).

In sum, both the PA and UA scales fit the RSM well. However the "state" level estimation was less well defined for UA. Despite this possible shortcoming the RSM provided a good representation of the item responses and allowed for the estimation of individuals' "true" levels of PA and UA across occasions on a scale with desirable measurement properties.

2.1.1. An alternative composite score measurement model. Of interest is how these RSM estimates might differ from the more simplistic composite scores used in other studies of weekly emotion. With our particular eight item scales and 179 individuals, the differences are relatively small. Across all persons and occasions RSM and composite scores correlated .99 for PA and .91 for UA, indicating that similar findings would ensue no matter which of the two measurement models was chosen. In fact, the results from all of the forthcoming analyses were almost identical when either the RSM or composite score measurement model was used. Results using the RSM are presented below. Correspondent composite score results are available from the authors upon request.

2.2. Interindividual Differences in Intraindividual Change—Cyclicity

2.2.1. Interindividual differences in variability. As a preliminary check we examined the PA and UA series for evidence of intraindividual variability to be sure that there were indeed some "state" changes that might be explained by a weekly cycle. Across persons, the average amount of intraindividual variability (intraindividual standard deviation or ISD of their detrended series) in RSM scores over 52 days was 0.63 (*SD* = .27) and 0.89 (*SD* = .30) for PA and UA, respectively. (*Note*: PA and UA are not on the same scale.) While some individuals showed more variability than others, all individuals exhibited day-to-day variation in both PA and UA that might be associated with a weekly cycle.

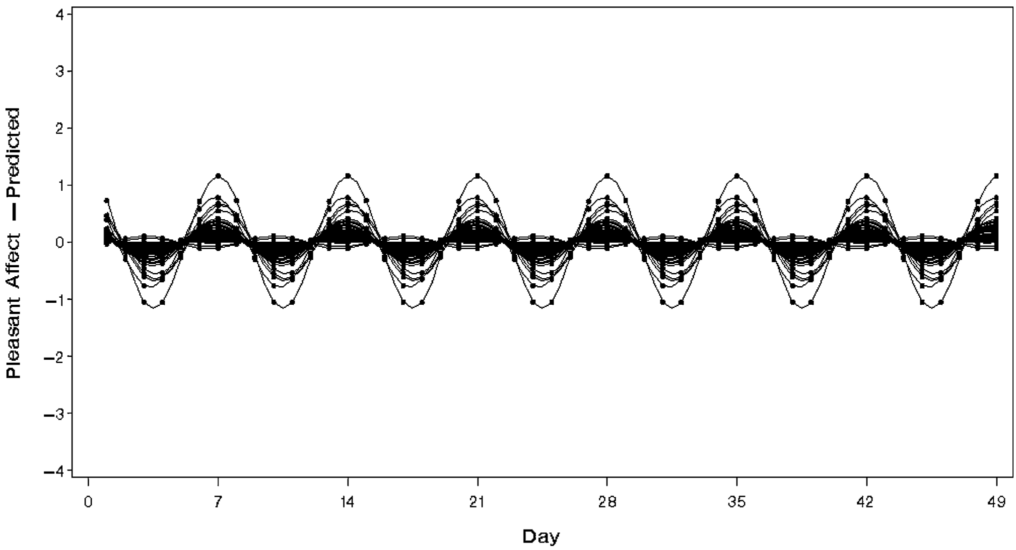

FIGURE 4.
Individuals' predicted weekly cycles for PA. Each individual is represented by a single line connecting their day to day emotional experiences.

2.2.2. Interindividual differences in the most prominent cycle. We used spectral analysis to determine the extent to which the day-to-day variability in individuals' emotions might be predominantly characterized by a weekly cycle. For each individual we obtained an estimate of which period accounted for the most variance in his or her PA and UA time series. The dominant cycle in individuals' PA ranged in period from 2 to 49 days, meaning that different individuals were characterized by different lengths of cycles or patterns. Similarly, the dominant cycle for individuals UA ranged in period from 2 to 49 days. Thus, there appear to be substantial individual differences in how individuals' PA and UA change over time, suggesting that a wide variety of characterizations of emotion are possible. However, cycles at or near 7-days accounted for the most variance in roughly a third of the individuals' PA series and a quarter of UA series.

2.2.3. Interindividual differences in weekly cyclicity. Multilevel models of change were used to fit individualized 7-day cycles to PA and UA. Results from the "simultaneous" and "multistep" fitting are shown in Table 1. Predicted curves are shown in Figures 4 and 5. As can be seen in the plots and as we noted in the spectral analysis results, there were substantial interindividual differences in how weekly cycles were exhibited.

The significant variability in amplitude, $u_{2i}(\sigma_2^2 = .04$ for PA, .05 for UA), indicates that individuals differ in the size of weekly fluctuations in their emotions. There were also notable interindividual differences in phase, u_{3i}, meaning that individuals differed on which day of the week their emotion was likely to peak. For PA, the mean value of $\phi(\gamma_{30} = .25)$ indicates a "prototypical" Saturday peak[4] ($\gamma_{20} = +.17$), and the variance estimate ($\sigma_3^2 = .06$) indicates that although the majority of participants' PA series' showed systematic peaks on Saturdays, some individuals exhibit peaks on other days of the week. For UA, ϕ estimates also showed substantial individual deviations ($\sigma_3^2 = .15$) from a "prototypical" Saturday ($\gamma_{30} = -.09$) valley ($\gamma_{20} = -.06$). Such results illustrate the finding that, across individuals, UA appears to exhibit less systematic patterns in its day-to-day progression than does PA.

[4]Phase shift, in radians, is converted to days, $= \phi(7/\pi)$.

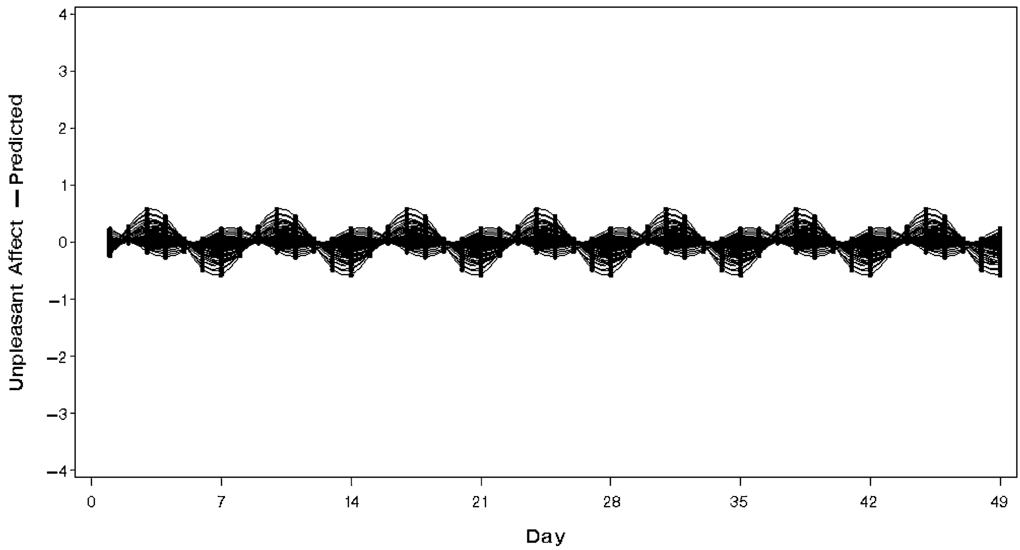

FIGURE 5.
Individuals' predicted weekly cycles for UA. Each individual is represented by a single line connecting their day to day emotional experiences.

2.2.4. Amount of variance accounted for by a weekly cycle. In random time series of length 52, a 7-day cycle is expected to account for 4% of the total variance in the series.[5] For our 179 individuals' 52 day time series data, a weekly cycle accounted for, on average, 6.3% ($SD = 10.3$) of their day-to-day variation in PA and 3.0% ($SD = 4.8$) of the it day-to-day variation in UA.[6] Only 77 of 179 persons exhibited discernable "entrainment" (i.e., percentage variance accounted for $> 4\%$) to a weekly cycle in PA and only 44 of 179 in UA. Thus, for most participants, a weekly cycle accounted for no more variance than we would expect if their emotions had been randomly determined.

2.2.5. Reliability of interindividual differences. To determine if the noted interindividual differences in weekly cyclicity were systematic, we assessed their reliability and examined how they were related to a number of other measured interindividual differences. Reliability of the interindividual differences in the cyclic change parameters was assessed by splitting the occasions of measurement into even- and odd-numbered days and conducting separate analyses on each individual's "parallel forms"—two time series with every other day missing. Reliability estimates were calculated by applying the Spearman Brown prophesy formula to the correlation between the parameters estimated from each split-half of occasions. Because phase is circular, with day 7 being close to day 1, these were transformed into linear angles using $\cos(\phi_i)$ so that they would more accurately reflect the distances between values.

The PA weekly cycle amplitudes, R_i, were relatively reliable ($\rho_{\mathrm{PA}} = .80$) and thus, could be considered reliable interindividual difference information. Amplitude parameters for UA were somewhat less reliable ($\rho_{\mathrm{UA}} = .51$), confirming, as we found with the measurement model, that the true characteristics of UA are more difficult to obtain. Nevertheless, both parameters carry reliable information.

[5]We calculated the average amount of variance accounted for by a 7-day cycle using 10,000 random time series of length 52.

[6]For each person we calculated a percentage of variance accounted for by the weekly cycle score. The mean and standard deviation reported here are of this distribution of scores.

Individual phase shift, $\cos(\phi_i)$, estimates, though, were not particularly reliable ($\rho_{\text{PA}} = .35$, $\rho_{\text{UA}} = .18$), suggesting that interindividual differences regarding which day of the week an individual's weekly cycle peaks cannot be clearly identified. Furthermore, this underscores that individuals' emotions do not follow "stationary" weekly cycles. The peaks of a cycle can seemingly occur at any time. That is, it appears that daily life events serve to continually shift the times when emotional peaks occur and may obscure underlying patterns. The model cannot discern which of these peaks might be due to the days of the week or to other events. Thus, any "true" weekly peak that may exist cannot be determined. It does, however, appear that an individual's amplitude (reactivity and to some extent entrainment) of a weekly cycle is discernable and can be estimated reliably.

2.2.6. Gender and personality differences in cyclic change. To further examine how systematic the individual differences in amplitude and fit might be, we examined their relationships with gender and individual differences in trait personality. Notable findings were that both the amplitude and fit of 7-day cycles were related to gender, with females exhibiting, on average, larger amplitudes in PA, $F(1, 150) = 8.17$, $p < .01$, $R^2 = .05$. Furthermore, amplitudes were associated with level of neuroticism (PA: $r = .17$; UA: $r = -.17$). These relationships, along with Larsen and Kasimatis' (1990) finding of a positive relationship between extraversion and entrainment (i.e., amount of variance accounted for), indicate that how individuals differentially exhibit weekly emotion cycles may be meaningful and interpretable interindividual difference information.

Overall, the spectral and multilevel modeling results indicate that there are some systematic individual differences in both the extent to which individuals' emotions follow a weekly cycle and in how such cycles are exhibited. Some individuals' data can be characterized by a weekly cycle and others' not so much. Some individuals show large, predictable, weekly swings in their emotions and others do not. Furthermore, it appears that the noted interindividual differences are to some extent dependent on the particular set of occasions sampled from any individual (e.g., even or odd occasions). Thus, it is not completely clear how a weekly cycle might progress for the "prototypical" individual, or perhaps even within a particular individual.

2.3. Comparison of Simultaneous and Multistep Procedures

"Simultaneous" model fitting for PA and UA took about 30 hours each on a desktop PC with a Pentium-4 2.0 GHz processor and 512 MB RAM. "Multistep" model fitting for PA and UA took a total of about 10 minutes each on the same computer. As can be seen in Table 1, the results are quite similar, with correlations between individual level parameters being between .92 and .99. Some benefits from using the simultaneous approach would be additional flexibility in model specification, streamlined and relatively unbiased estimation, the use of latent variable "true scores" in the nonlinear regressions, and the possibility of incorporating prior information (in the Bayesian framework). Some benefits of using the multistep approach would be specialized fit statistics, accessibility of software, and considerably reduced computer run time.

2.4. Simulation Results[7]

The simulated data were fitted using multistep fitting procedures. True item and cyclic change parameters were recovered with reasonable accuracy. In some cases there was a discrepancy between the true period of oscillation and the estimated value—likely due to "leakage" (where the number of observations is not an integer multiple of the cycle length) and which is to be expected

[7]Only brief summaries of the simulation and incomplete data results are included here. A more extensive report is available from the authors upon request.

when working with a fixed number of time points. Further exploration using varying lengths of the available observations (e.g., 48 days, 47 days, etc.) would likely lead us to the true periodicity (Warner, 1998). However, and for our purposes more importantly, with 49-occasion series we were able to accurately identify 80% of those individuals who were predominantly characterized by the cycle length of interest—a 7-day cycle. With the subsequent confirmatory model fitting the simulated individual differences in the characteristics of 7-day cyclicity (i.e., amplitude and phase shift) were recovered with reasonable accuracy (correlations of true and estimated parameters being $\sim .7$), even in the presence of measurement error and dynamic "noise" (i.e., other cycles or "concurrent processes"). Overall, the simulation provided evidence that applying the RSM and cyclic change models together is a viable method of identifying both qualitative (i.e., predominant cycle length) and quantitative (i.e., amplitude, phase) individual differences in cyclicity, and that the analytic approach could be similarly applied to other longitudinal data sets to identify if and how the measured processes might be characterized by cycles.

2.5. *Incomplete Data Conditions*[7]

2.5.1. Random incompleteness. When a percentage (e.g., 10%, 20%, 40%, 60%, 80%) of person-occasions were randomly dropped from the empirical data, item characteristics were still recovered with high accuracy. With up to 20% incomplete data, the combined analysis technique (RSM and weekly cycle fitting) was robust. Individual differences in cyclicty could still be identified with a reasonable level of accuracy. However, as incompleteness increased further (i.e., $> 20\%$) the inaccuracy of "state" estimates obscured the "true" interindividual differences information, particularly in the phase shift. Overall, these findings suggest that even though longitudinal emotion data are often incomplete, as long as measurements are obtained on at least 80% of occasions representative individual differences in cyclicity might still be obtained.

2.5.2. Planned incompleteness. When the data were configured as though individuals had only been presented with either two or four randomly selected items on any given occasion, item characteristics were still recovered with high accuracy. Even when only two items had been used to derive "state" estimates of PA and UA the individual differences in cyclicity were identified with a reasonable level of accuracy. Such results suggest that emotion sampling questionnaire lengths could be reduced substantially. Only a few randomly selected items from a larger item pool may be necessary to obtain information regarding individual differences in cyclicity.

3. Discussion

The purpose of this analysis was to examine if and how individuals' emotions may be characterized by a weekly cycle. Using daily reports of emotion experiences we obtained estimates of individuals' day-to-day pleasant and unpleasant emotional states and attempted to extract patterns of weekly cyclicity from them. Generally, we found that "true" score estimates of PA and UA could be derived from these particular 16 items, and that there are substantial individual differences in both the extent to which individuals' emotions follow a weekly cycle and in how such cycles are exhibited.

It is encouraging that our eight-item scales had the desirable measurement properties required by the RSM. This meant that "true" score estimates derived from the measurement model could be considered accurate representations of underlying "state" levels of affect. However, the response category thresholds indicated that a 7-point scale may not be necessary. The same amount of information could possibly have been obtained with a more parsimonious 5-point scale.

Furthermore, results from the analyses of incomplete data indicate that interindividual differences in cyclicity can be recovered with a high degree of accuracy using as few as two randomly selected items per measurement occasion. Thus, scales for use in forthcoming studies of intraindividual variability in emotion and subjective well-being might be constructed using fewer items with fewer response options.

The spectral analysis and sinusoidal change findings (e.g., Table 1, Figures 4 and 5) highlight the high degree of heterogeneity in how individual emotional experience progresses over time. There is, at least with respect to the days of the week, great diversity in the timing of mood fluctuations. For example, weekly cycles do not "define" how all individual's emotions progress from day-to-day or week-to-week. For only a portion of the sample was the 7-day cycle the predominant one. Other individuals' emotional experiences were better characterized using other periodicities. In other words, there is no clear "prototypical" pattern of cyclicity.

The substantial interindividual differences noted in the sinusoidal model parameters further highlight that weekly cyclicity is not a particularly prominent feature in our data. Weekly sinusoids, for most individuals, accounted for relatively little of the variation in day-to-day emotions and suggest that current notions regarding the strength of a weekly mood cycle should be reconsidered. While the analysis of aggregated data (e.g., first analysis in Larsen & Kasimatis, 1990) has been interpreted as "accounting for 40% of the variance in daily mood ... strongly support[ing] the existence of a weekly mood cycle" (Croft & Walker, 2001), this is likely true only at the group level. At the individual level, we find the prototypical weekly cycle to be much more obscure. The essential point that we hope to have illustrated here is that care should be taken in the aggregation of individuals and the generalization of results (see, e.g., Estes, 1956; Molenaar, 2004, for further explication of this point).

Overall, we found that individuals' emotions do not follow clean weekly cycles. Our initial hypothesis was that individuals' emotions are in part determined by a weekly cycle. Certainly, though, emotions are affected and determined by many other things as well. For instance, random or even expected events, hormones, weather, and seasonal cycles all affect one's current emotional state (e.g., Murray et al., 2002; Reid et al., 2000; Rusting & Larsen, 1998). Thus, at any given point in time, one's self-reported levels of emotion are more likely to be an amalgamation of responses to a multitude of internal and external factors. There may be a variety of factors or "shocks" that propel individuals away from the confines of their own dominant cycles, and thus lead to *intraindividual* shifts, or nonstationarity, in periodicity. Furthermore, with all of these factors shifting in both systematic and unsystematic ways over time, the underlying patterns our simplistic representations hope to capture will likely be obscured. Time-varying models that allow for explicit modeling of such within-person variability in periodicity (and in other parameters) may in the future be able to provide more comprehensive representations of inherent complexity of emotion dynamics. Generally, that we were able to extract reliable and systematic information about the heterogeneity of persons from relatively noisy data using relatively simplistic representations of behavior suggests that further examination is warranted.

Throughout our analysis we assumed that the item response process (measurement model) and the dynamic process (change model) were independent of one another. Although this assumption is commonly made, albeit often implicitly (e.g., modeling composite scores), this is a strong assumption that may or may not be correct. Other applications of the general analytic approach described here should, on the basis of theory and previous research, carefully consider the item response process and its associated measurement model, the dynamic process and its associated change model, *and* possible interactions between the item response and dynamic processes. For example, in our planned incomplete data analysis we partially addressed how the item response model might change over time as individuals responded to the same battery of items over and over and over again (e.g., item drift). We proposed a data collection format that could potentially alleviate such drift. Furthermore, we could and should consider how the item response model might change over time (e.g., person dependence at the item level), the possibility of alternative (e.g., sawtooth waves with unequal rise and fall times) or additional (e.g., exam or menstrual cycles, linear trend) characterizations of change, and how the item response process may be affected by where individuals happen to be in their dynamics (e.g., differential item functioning between the peaks and troughs of cycles—which might occur at different times for different individuals). All such possibilities should be taken under consideration and a plausible model (or combination of models) tested.

In pursuing our analysis objectives, measurement, change, and individual differences were addressed by combining an item response analysis with a frequency-domain analysis. But, this is only one manner of addressing these practical issues. Other methods or combinations of methods might be used effectively as well (e.g., factor models and ARMA time series models, Browne & Nesselroade, 2005). From a statistical perspective it would, in most cases, be better to fit the measurement model and change model simultaneously. However, the computational time associated with simultaneous fitting may not be practical in some modeling contexts. Thus, we have also presented a "multistep" alternative. Our comparisons and simulations give us some level of confidence that the alternative serves as a reasonable proxy for the more streamlined analysis. With the tools of the future we look forward to being able to conduct such an investigation with both speed and elegance.

Using current and widely available techniques we illustrated how models from different modeling traditions might be coupled together to obtain richer descriptions of human behavior. The RSM was used to examine the patterns that existed among items and to provide an objective scale of measurement. Spectral analytic techniques were used to examine the cyclic change in individuals' daily pleasant and unpleasant affect. Together, these methods allowed us to learn more about emotional experience while illustrating how multiple techniques can be combined to capitalize on the strengths of each.

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